Identification of parameters and phenomena of hydrological restoration processes in lowland bog areas using ERS-SAR data

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Abstract

A pixel-based neural network classification of a multi-temporal ERS-1 and ERS-2 SAR data set in a mainly grassland area in Brandenburg Germany is presented. The results are preliminary but give hope on an alternative way to deduct restoration recommendations for a former wetland area as opposed to a hydrological approach based on a DTM and ground water table depths which serves as a comparison.

Keywords: SAR data, classification, neural network, biotope types

Introduction

The renaturalization and rewetting of formerly drained low moor areas in northeast Germany can only be achieved based on detailed knowledge of the occuring organic and mineral soil substrates, the terrain characteristics and the available surface and groundwater resources.

A research project funded by BMBF (Dietrich et al. 1996; Dietrich 1995; Dietrich, Dannowski & Quast 1995; see also acknowledgement) analysed the possibilities of renaturalization of three different areas in the state of Brandenburg one of these was the area Rhinluch and delineated areas are preferable for rewetting and thus restoreation of the former status. This analysis was based on a DTM (digital terrain model), extensive measurements of the hydraulic characteristics of the area and hydrologic model. The ecological development concept of the same area was provided by (Kretschmer et al. 1995).

Since the necessary field measurements are costly and time consuming, it is tried to reach the same recommendation results on the basis of ERS DATA, which is partly represented here, and LANDSAT-TM data as to analyses the contribution of optical satellite data for this purpose and possible disadvantages and/or benefits. Related work in nortwest Germany can be found in (Reinke 1995) and (Schelling 1996). The method developed for Rhinluch is going to be transfered to two other study areas in northeast Germany (Finow Valley near Eberswalde and Friedland Great Meadows near Torgelow).

Material

A local GIS of the investigation area Rhinluch, includes a biotope and landuse map with 17 classes: forests on mineral soils, decideous trees on moist to wet sites, riverine woods, shrubs on moist and wet sites, undergrowth on moist to wet sites, tall herbaceous plants, high diversity pasture on wet sites, high diversity pasture on variably wet sites, fallows on wet sites, fallows on variably wet sites, sowed grassland, sedge, reeds, aquatics with floating leaves, agriculturally used areas, towns and buildings, lakes and ditches.

A soil map with 9 subclasses shows the heterogeneity of organic and mineral soils in the area. The digital terrain model calculated from 12 topographic maps in the scale 1 : 10 000 and the measured ground water table depth which was acquired during field campaigns was used to calculate the possible rewetting areas during the planned renaturalization process.

The image data were acquired from April 1995 to April 1996 by ERS-1 and ERS-2 so that a time series of 17 data takes of geocoded and terrain corrected products (GTC) is available. The full scenes converted to 8-bit data keeping track of the linear scaling parameters, were then subsetted and the subscenes of the region of interest were coregistered according to their common UTM coordinates. The image stack was then transformed into a transverse Mercator reference system with Gauss-Krüger net and Bessel ellipsoid for easy comparison and overlay with the GIS data. A LEE-filter with a 5x5 window was applied to the image data in order to reduce image speckle. Here a preliminary analysis with a neural network approach for biotope type classification are presented.

Method

Based on the reference data (biotope type map, figure 1) and optical data from LANDSAT-TM, the distinguishable biotope types were delineated on the image to extract sample areas. The use of additional optical data was appropriate, because the reference map seemed to be generalized to an inappropriate degree. This was especially the case in built-up areas, where gardens and shrubs were mixed with this class also.

During this analysis it was obvious that especially those biotope types that occur only in small areas or enlongated fringes are not suited for the classification due to their low spatial extension (undergrowth on variably sites, aquatics with floating leaves).

Therefore only the following 15 classes were extracted: forests on mineral soils, deciduous trees on variably wet sites, riverine woods, shrubs on moist and wet sites, tall herbaceous plants, high diversity pasture on wet sites, high diversity pasture on variably wet sites, green fallows on wet sites, green fallows on variably wet sites, sowed grassland, sedge stands, reed stands, agriculturally used areas, towns and buildings, lakes and ditches.

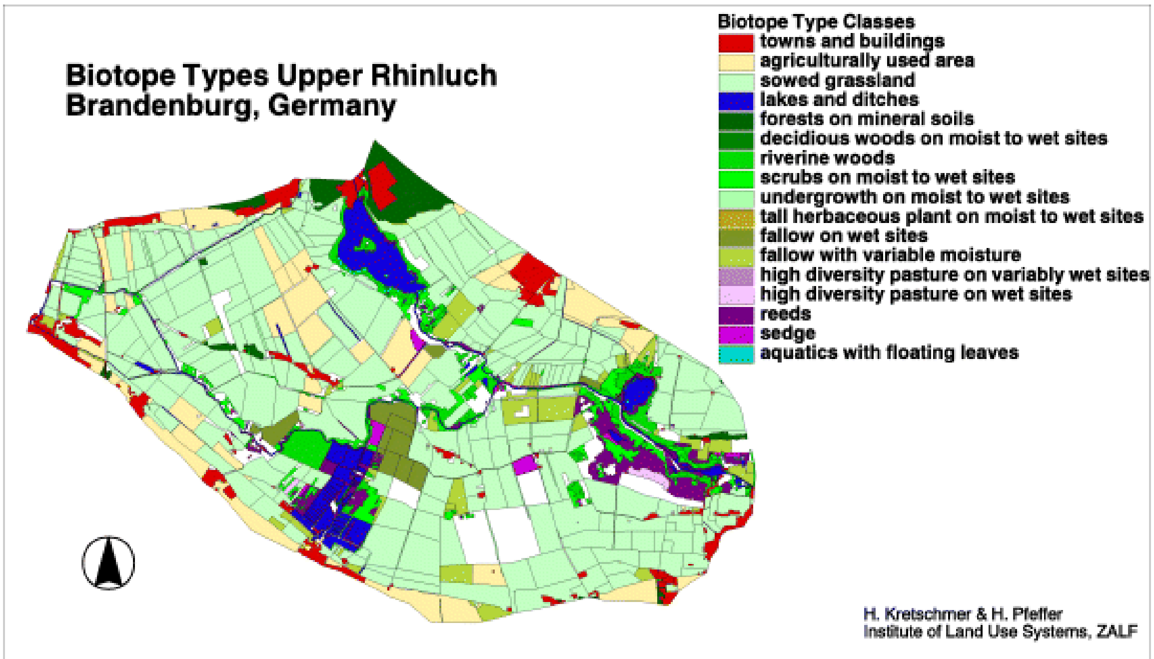

Figure 1: Terrestric biotope type reference map.

The overall number of sample areas was 290 which is about 5% of the investigation area. The normalized mean and the standard deviation (values ranging between 0...1) were used as input patterns for the neural network approach. The coding of the output patterns was achieved by a 1-out-of-n-coding, that means the unit that equals the class number is assigned a value 1.0, whereas all others receive the value 0.0. The applied neural network approach was a backpropagation network with momentum term in online mode which is an implementation of the University of Stuttgart (SNNS software package). A learning rate 0.01 was used, while the momentum term was set to 0.9. The activation function had sigmoidal characteristics. Learning was stopped after 1000 epochs. The applied network architecture was 30-30-15, i.e. 30 input units due to two parameters per image layer (mean and standard deviation for each of the 15 dates), one layer of 30 hidden units and 15 output units due to the formerly specified 15 desired classes.

For the final classification of the image data set a 5 by 5 window was moved across the image to calculate the mean and standard deviation in the neighborhood of the center pixel over all image layers (dates). The results were fed into the trained neural network, in which the unit with the highest output value formed the new class value.

Results

This classification was a first approach which still has to be refined. The classification results are shown in Fig. 2 and Fig. 1 the actual biotope types from the aerial image interpretation and field investigations by (Kretschmer et al. 1995) can be compared to this.

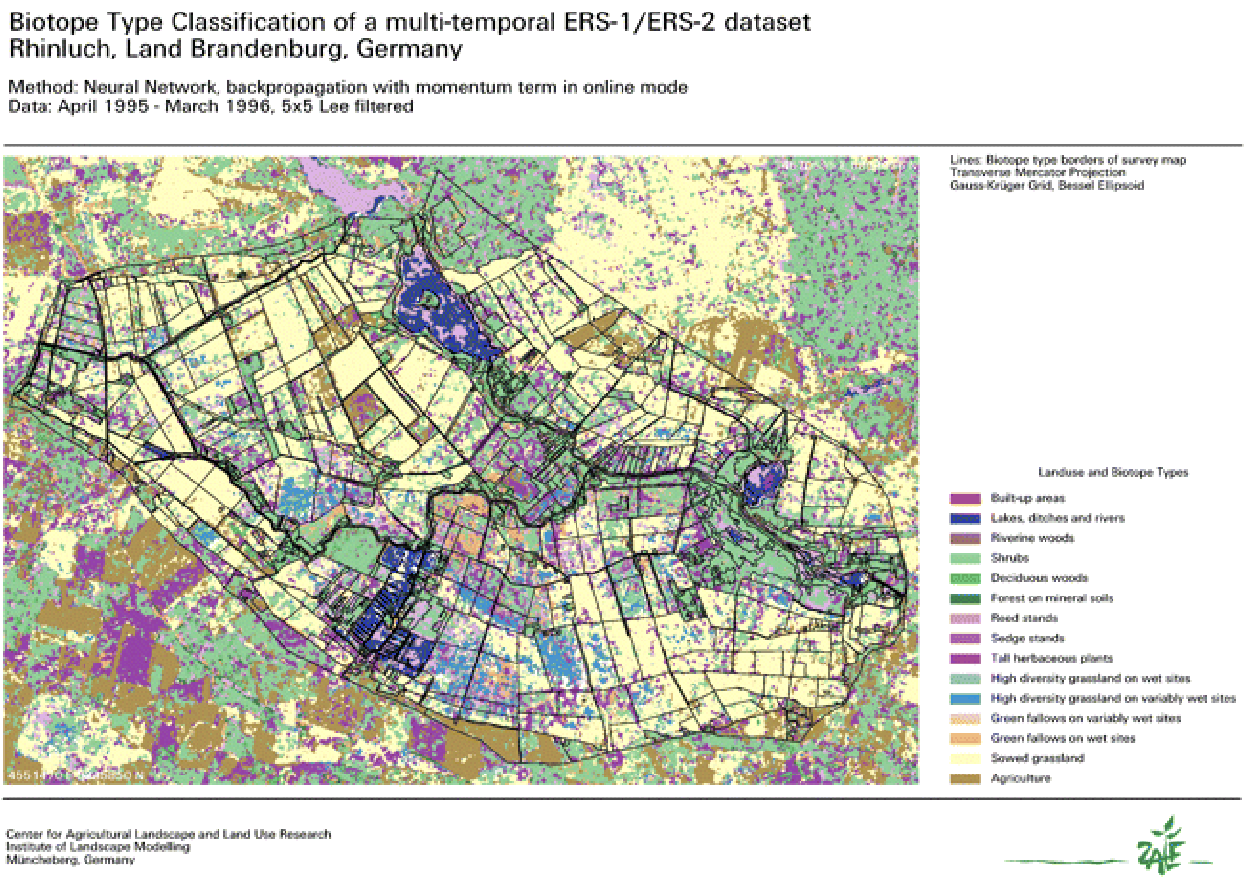

Figure 2: Neural Network classification results of biotope types. Click for 825x600 or 1100x800 resolution.

Visual interpretation of the classfication results shows that most of the area is dominated by sowed grassland, which has been well recognized by the neural network approach pretty well. Also, the lakes received the correct class assignment, except for the long lake in the upper middle of the image, which was totally misclassified as reeds. The misclassification of the other areas are partly due to missing training patterns (areas outside the polygon overlay) for which no land use information was available.

The overall confusion matrix in Tab. 1 was created using the full investigation area (field based reference map) and the neural network classification. For each reference class the percentage of misclassifications was counted. It is striking that shrubs, sowed grassland, agriculture and tall herbaceous plants were best recognized. Most of the forest on mineral soils was misclassified as shrubs. Also between the different grassland types a high confusion can be recognized. This is not too surprising, because the geometry of the plants is nearly the same. Herein the demand for the design of more geometry oriented classes arises.

		Classes after Neural Network Classification															
	Field data	**1**	**2**	**4**	**5**	**6**	**7**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**Sum**
0	Background	0.60	0.12	3.32	32.87	4.65	3.02	1.27	0.12	15.29	2.48	0.36	0.48	3.93	15.53	15.95	100
1	Built-up	3.27		7.62	39.38	9.44	4.17	1.63	0.91	7.26	1.45		0.18	2.00	9.26	13.43	100
2	Lakes, ditches and rivers	50.00				50.00											100
3	Aquatic with floating leaves																
4	Riverine woods																
5	Shrubs	6.12		16.33	57.14	4.08				2.04	2.04		6.12		4.08	2.04	100
6	Deciduous woods																
7	Forest on mineral soils			2.48	53.96	8.42	3.96	0.99	0.50	17.82	0.99	1.98		4.46	1.49	2.97	100
8	Undergrowth				25.00	25.00									50.00		100
9	Reed stands																
10	Sedge stands																
11	Tall herbaceous plants			4.00	12.00	9.33	2.67			36.00				13.33	9.33	13.33	100
12	High diversity grassland, wet sites																
13	High diversity grassland, variably wet sites	12.50													87.50		100
14	Green fallows, variably wet sites				23.68	10.53	6.58			17.11	1.32			14.47	14.47	11.84	100

15	Green fallows, wet sites																	
16	Sowed grassland				23.39	1.02	1.02	5.76		12.88	1.36		1.02	1.69	40.00	11.86	100	
17	Agriculture			0.36	29.04	0.91	2.18	0.36	0.54	21.23	3.27	0.91	0.36	2.36	13.25	25.23		

Table 1: Results of the neural network classification approach on test site Rhinluch, Germany. Comparison of full investigation area.

Class assignments are given in %. Classes 3 and 8 were not present in the neural network approach.

Conclusions

The classification results are promising, but have to be further improved by data set optimisation (selection of most significant images) and by the application a more advanced neural network approach that takes into account neighboring pixels at the design of the training patterns.

Moreover the transferability to other investigation areas and the comparison with optical data classification of biotope types with conventional and neural network approaches will be investigated within the scope of AO2.128.

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